Comparison on Sensor Fault Detection Techniques for SHM Systems

JAN-HAUKE BARTELS, SOREN MEYER ZU WESTERHAUSEN, THOMAS POTTHAST, MICHAEL BEER, STEFFEN MARX and ROLAND LACHMAYER

ABSTRACT

Engineering systems are designed to serve society for decades and are exposed to multiple environmental and load conditions. This circumstance leads to the degradation of the system, causing different structural behaviours. In this regard, monitoring systems can assess structural health by recording time-dependent structural behaviour through a network of measurement instruments. However, monitoring systems can be affected by changing external conditions, leading to sensor degradation and faults that produce plausible data but incorrect information about the structural condition. Therefore, distinguishing between sensor faults and structural damage is critical to ensuring the reliability of SHM over the lifetime of the structure.

Different techniques with varying effort and complexity could be used, such as linear regression, Mahalanobis distance, or multiple neural network architectures, to identify sensor faults. This study investigates the suitability of these techniques regarding the accuracy of sensor fault detection and computational effort on the example of a steel specimen equipped with nine strain gauges in a 3-point bending test with a cyclic load. In the test, one of the nine sensors showed a signal drift, which needs to be detected in a monitoring application using these sensor fault detection techniques.

The results show that for this simple test, the Mahalanobis distance is the fastest and most accurate, while the linear regression technique is very fast but very imprecise, and the artificial neural network is relatively accurate but very slow. However, all the techniques used showed the potential to significantly increase the robustness of the monitoring system, which is important for more complex engineering structures.

Keywords: Artificial Neural Network; cyclic loading; linear regression; Mahalanobis distance; sensor ageing; sensor fault detection; strain gauge measurement; Structural Health Monitoring

INTRODUCTION

In recent years, structural health monitoring (SHM) has gained increasing interest in various applications like aerospace components [1], wind turbines [2], bridges [3], and many more. One way to do so is by applying strain gauges as sensors, which could yield information on structural behaviour and operational loads [4, 5]. To monitor larger structures and areas, reliably working sensor networks are necessary [6]. For this, it is essential to include detection of sensor failures, e. g., due to signal drift, into evaluations

Jan-Hauke Bartels, Email: bartels@lpi-ing.de. LPI Ingenieurgesellschaft mbH, Hannover, Germany.

of the SHM system's reliability analysis. Different techniques are presented in the literature for such sensor fault detections, which all have their advantages and disadvantages when it comes to the implementation effort, computational speed, and scalability for complicated relations between sensor measurements. Therefore, this paper aims to investigate and compare three different sensor fault detection techniques for SHM systems on real-world measurements of strain gauges on a steel structure.

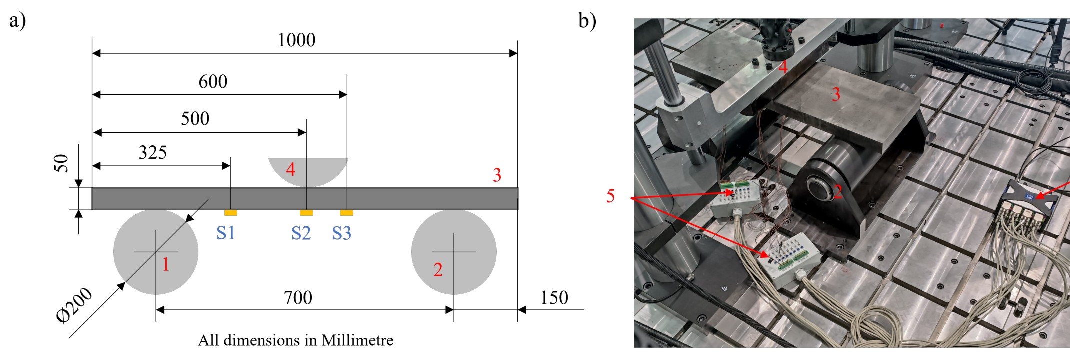
To do so, this paper's structure is as follows. After this Introduction, the next section presents the experimental setup under investigation and the background of applied techniques for sensor fault detection. After this, these sensor fault-detection techniques are applied to the experimental data, and the results are compared. The last section concludes the results and gives a brief outlook for future work.

EXPERIMENTAL SETUP AND METHODOLOGY

Experimental setup

The data for this study is generated from a real-world test case on the multi-axial test rig in the SCALE research building of the Leibniz University Hannover, Germany. This test case, a scaled 3-point bending test, is carried out using a rectangular steel component made of S235JRC+C (1.0038) with the dimensions of 1000 mm x 300 mm x 50 mm. This specimen is subjected to a bending load in the form of a sinusoidal load between 0 kN and 100 kN with a load frequency of 10 Hz, applied by a servo-hydraulic test cylinder with a maximum static force of 110 kN. Besides, the specimen lies on two rotatable bearing blocks of 200 mm diameter each, as shown in Fig. 1.

In this setup, three sensor lines (marked yellow as S1, S2 and S3 in Fig. 1) are used, where three strain gauges of type HBM 1-LY11-6/120 are applied equidistantly on each line. Therefore, each sensor at each line faces the identical strain amplitudes and their signals are recorded by an HBM QuantumX840B data acquisition system with 100 Hz sampling rate, where data is saved every 60 minutes. For a single strain gauge, quarter bridge completions manufactured by SincoTec Test Systems GmbH are used to form a



1, 2: Bearings; 3: Specimen; 4: Load application; 5: Quarter bridge completion; 6: Data acquisition system; S1-3: Lines with sensors

Figure 1. Experimental setup as 3-point bending test. (**a**) Sketch of the experimental setup; (**b**) photo of the test setup carried out on the multi-axial test rig at the SCALE research building.

Wheatstone bridge. This test was carried out for 9'151'833 load cycles and ended with a control error, which resulted from an out-of-range way of the test cylinder due to plastic deformation of the specimen.

Methodology

Sensor faults represent a critical challenge in SHM, as they can lead to misinterpretation of structural conditions and consequently to incorrect maintenance decisions. The process of sensor fault diagnosis generally comprises four key steps: (i) detection, (ii) localization, (iii) classification, and (iv) compensation [7, 8]. This study focuses specifically on sensor fault detection in sensor networks.

Several previous studies, including those by Al-Zuriqat et al. [9] and Lydakis et al. [10], have addressed sensor fault diagnosis using structure-specific, deterministic thresholds. While these methods have succeeded in certain applications, their reliance on fixed thresholds tailored to individual structures limits their generalizability and increases the likelihood of false positives or negatives in different settings. To address these limitations, a probabilistic thresholding approach for reliable sensor fault detection is used in the following, which is evaluated using three different analysis methods: (i) Linear regression, (ii) Mahalanobis distance, and (iii) Artificial Neural Networks. Each method is briefly introduced and extended to incorporate probabilistic sensor fault detection. Central to the proposed methodology is the comparison between a known, undamaged reference state and a new, potentially faulty comparison state. This reference-probabilistic-based evaluation forms the foundation for robust and transferable sensor fault detection across varying structural systems.

The first method analysed in this study applies linear regression to detect sensor faults based on an analytical redundancy approach. Instead of relying on hardware redundancy (e.g., co-located sensors), this approach exploits the strong correlation between spatially adjacent sensors. In the case study presented here, signals from sensors S1-1 to S3-3 are used, with one or several sensor signals acting as the predictor and one sensor signal as the response variable. The regression model is trained using ordinary least squares on a reference dataset representing the healthy structural and monitoring system condition. The dataset is split into 80 % for training and 20 % for testing, with 5-fold cross-validation applied to the training portion to avoid overfitting and to enhance generalization. Model accuracy is quantified using the mean squared error (MSE):

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2, \tag{1}$$

where y_i are measured values and $\hat{y}_i$ are predictions. To define a probabilistic threshold for sensor fault detection, the MSE is computed for equidistant time windows within the reference dataset (e. g., 100 seconds total duration), yielding a distribution of MSE values. Assuming approximate normal distributions based on the central limit theorem, the 99.73 %-quantile (mean + 3 standard deviations) is selected as the detection threshold. When evaluating new data, a sensor fault is inferred if the windowed MSE exceeds this probabilistic threshold from the reference state. This high-confidence threshold minimizes false positives in the healthy state while ensuring sensitivity to significant deviations.

The second method considered in this study is the Mahalanobis distance, a well-established technique for outlier detection in multivariate data [11]. For probabilistic sensor fault detection, the Mahalanobis distance quantifies the distance between a given observation and the mean of a reference distribution, while accounting for the correlations between variables [12]. This is particularly relevant in sensor networks, where measurements from different sensors are often correlated. Unlike Euclidean distance or z-score-based approaches, which ignore inter-variable dependencies, the Mahalanobis distance incorporates the full covariance structure of the reference state, making it well-suited for detecting anomalies in multivariate sensor data [13]. Given a multivariate dataset with n observations and p correlated variables, the Mahalanobis distance Δ between a new observation vector $\vec{x}$ and the mean vector $\vec{\mu}$ of the reference state is defined as

$$\Delta = \sqrt{(\vec{x} - \vec{\mu})^T S^{-1} (\vec{x} - \vec{\mu})}, \tag{2}$$

where S^{-1} is the inverse of the covariance matrix of the reference data. This transformation effectively removes correlations, normalizes the data, and allows for distance measurement along the principal axes of the distribution. A sensor fault is detected if the computed Mahalanobis distance exceeds a threshold derived from the chi-squared distribution $\chi^2_{p,\alpha}$. For two variables (i.e., $p = 2$) and a significance level of 5 %, the threshold is 5.99. Observations exceeding this probabilistic threshold are considered statistically improbable under the reference state and are classified as sensor faults.

The third method explored in this study leverages artificial intelligence, specifically Artificial Neural Networks (ANNs), for sensor fault detection. Due to their ability to model complex, non-linear relationships between multiple sensor inputs, ANNs are well-suited for predicting expected sensor behaviour and identifying deviations indicative of faults. In a typical ANN architecture, sensor measurements X are fed into an input layer, processed through one or more hidden layers, and yield predicted outputs $\bar{y}$ from the final output layer.

This relationship can be described by:

$$\bar{y} = f(X, \theta), \tag{3}$$

where θ describes the model parameters and weights in the layers.

The application of ANNs for sensor fault detection in SHM has been demonstrated in prior research. For instance, Al-Zuriqat et al. [9] employed ANNs to detect six different types of sensor faults in a railway bridge monitoring system. In their approach, a dedicated ANN was trained for each sensor in the network, taking measurements from surrounding sensors as inputs. Deviations between the predicted and actual measurements were used to identify and classify sensor faults. However, their approach primarily focused on sensor fault diagnosis with deterministic thresholds. In this study, the approach is extended by the definition of a probabilistic threshold to enable the generalizability of the approach by applying it to arbitrary SHM systems.

In this study, a simplified ANN model is implemented in Python using the Keras framework. The model is structured as a fully connected neural network with one input neuron per sensor, followed by two hidden layers of 16 neurons each, using ReLU as the activation function. For each time window t, the ANN processes the sensor output a binary indicator (0 or 1) per sensor, signalling whether a fault is detected. Therefore, the sigmoid activation function is used for the output layer, which is well-suited for this type of classification output. The network is trained in the same way as the linear regression model. Deviations from learned patterns in the comparison state are flagged as potential sensor faults, enabling data-driven, probabilistic sensor fault detection.

ANALYSIS OF SENSOR FAULT DETECTION

The following analysis evaluates the effectiveness of the three above-described sensor fault detection techniques, using both qualitative and quantitative assessments of selected sensor signals. Each method incorporates a probabilistic threshold to distinguish between healthy and faulty sensor behaviour. To maintain clarity and focus, only a subset of three sensors is used from the available network of nine. This selection can illustrate the methodology without overloading text and figures with excessive data. The selected sensor signals are S1-1, S2-1, and S3-1 with the corresponding raw data shown in Fig. 2. These sensors are chosen since they are positioned similarly on their corresponding lines, and sensor S2-1 showed signal drift in the experiment.

Differences in strain amplitude among the sensors could be observed, which are consistent with the expected strain distribution in a 3-point bending setup. Sensor S2-1, located at the load application point in the specimen's middle on the bottom surface, records the highest strain amplitude with $\Delta\epsilon = \pm 170$ μm/m. Sensors S3-1 and S1-1 register lower amplitudes of ± 115 μm/m and ± 110 μm/m, respectively. These variations align with elasticity theory, which predicts the maximum tensile strain at mid-span and lower strains near the support points. The positive strain values are also expected, as tensile deformation occurs on the bottom surface of the specimen during bending.

A closer look at the data reveals periodic signal fluctuations caused by the sinusoidal loading of the test machine. With an excitation frequency of 10 Hz and a total number of 9,151,833 load cycles, the experiment ran continuously for 10.6 days until the specimen underwent fatigue-induced plastic deformation and the test was automatically terminated. Notably, Sensor S2-1 exhibits a significant drift over time, whereas the other two sensors remain stable. This behaviour indicates a likely sensor fault in S2-1. To

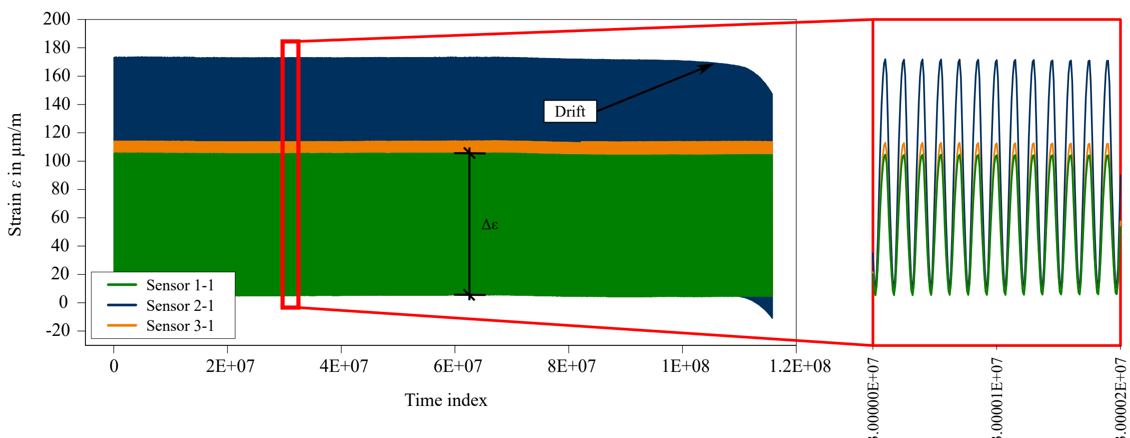


Figure 2. Strain measurement signals of the three chosen sensors in this study with sinus-like strain-over-time signals and signal drift of sensor S2-1.

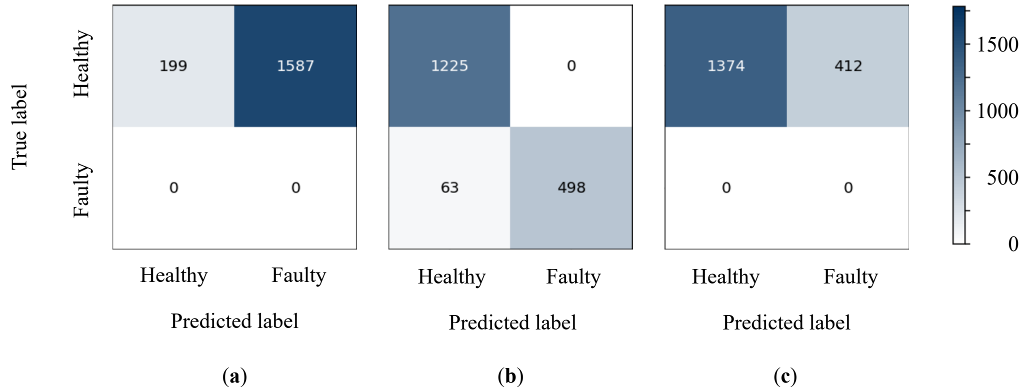


Figure 3. Confusion matrices for the three analysis methods investigated. (**a**) Linear regression; (**b**) Mahalanobis distance; (**c**) Artificial Neural Network.

ensure reliable structural condition assessment, this faulty sensor must be excluded from further mechanical evaluation of the steel specimen.

The objective of the sensor fault detection method presented in this paper is to identify this drift quickly and reliably. To do so, a reference state of the healthy measuring system and component state is defined. For the present data set, only one day (24 hours) at the beginning of the test of the total 10.6 day test period is used as a reference to evaluate the remaining 9 days with regard to sensor faults. An overview of the detection accuracy is given in Fig. 3, which shows the confusion matrices for the three techniques.

Fig. 3 (**a**) illustrates that the linear regression approach results in a high number of false positives (1587), indicating sensor faults even though no actual faults are present. This poor detection performance has practical consequences: SHM systems may be unnecessarily deactivated and subjected to manual inspection, causing avoidable maintenance efforts. Furthermore, the credibility of the SHM system among engineers responsible for structural assessment can be significantly undermined. In contrast, the Mahalanobis distance approach, shown in Fig. 3 (**b**), demonstrates strong robustness in detecting sensor drift. Only 63 false negatives are observed, meaning that in these cases, a sensor fault occurred but went undetected. The ANN approach, illustrated in Fig. 3 (**c**), exhibits a moderately lower detection performance than the Mahalanobis distance method, yet still shows promising results overall.

The quantitative evaluation is carried out with Table I, in which the detection accuracy and the computing speed of the approaches are compared with each other. From this comparison, it becomes clear that linear regression showed a very low accuracy, while being comparably slower in calculation than the Mahalanobis distance approach.

TABLE I. Detection accuracy and computational speed of the three analysed sensor fault detection techniques.

	Accuracy	Calculation time
Linear Regression	11.14 %	105.30 s
Mahalanobis distance	96.47 %	35.51 s
Artificial Neural Network	76.93 %	5112.27 s

In contrast, the Mahalanobis distance showed a high accuracy of over 96 % while being the fastest of the investigated techniques. The ANN also has a significantly poorer detection accuracy compared to the Mahalanobis distance approach, with an accuracy of less than 77 %. In addition, the ANN takes a very long time to train for the large data set. However, the ANN was tested in a first version with a non-optimised architecture and one investigated activation function, so other variants might lead to better results.

Therefore, it becomes clear that more advanced techniques like the Mahalanobis distance and ANNs are more suitable for reliable sensor fault detection. Especially when there is a very low tolerance for prediction errors for sensor faults, for example, in critical infrastructure applications, the Mahalanobis distance is the best choice.

CONCLUSION AND OUTLOOK

Robust SHM strongly depends on the correctness of sensor data to make the right decisions. In case sensors are ageing and signal drift or other faults occur, hazardous consequences might occur, which makes sensor fault detection a topic of great importance. In this paper, three techniques for sensor fault detection (linear regression, Mahalanobis distance, and ANN) were tested on data from a steel specimen in a 3-point bending test, where one of nine strain gauges showed signal drift. For this, a sensor fault is considered present for these techniques if a certain value for a set of sensor data exceeds a probabilistic threshold. The results show that linear regression performs poorly, while the ANN and the Mahalanobis distance work well on the considered test case.

Future work will extend the analysis to more complex structures with distributed sensor networks, where linear regression may reach its limits. In this study, only a simple plate-like specimen with constant cross-section and cyclic loading was considered. Additionally, using fixed time windows and static sensor configurations for probabilistic threshold estimation will be re-evaluated using varying window sizes and sensor setups. The applied ANN will be further developed, including tests with different activation functions and architectures like graph neural networks. Moreover, while this study focused on simple drift faults, future work will include other fault types such as bias and amplitude gain.

All in all, the proposed method contributes to more reliable condition assessments of load-bearing structures, facilitating improved decision-making and promoting long-term sustainability in SHM.

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DATA AVAILABILITY

The data used for this study is available in the Research Data Repository of the Leibniz University Hannover at [14].

REFERENCES

1. S. Abbas, F. Li, and J. Qiu, "A review on shm techniques and current challenges for characteristic investigation of damage in composite material components of aviation industry," *Materials Performance and Characterization*, vol. 7, no. 1, pp. 224–258, 2018.
2. P. Kaewniam, M. Cao, N. F. Alkayem, D. Li, and E. Manoach, "Recent advances in damage detection of wind turbine blades: A state-of-the-art review," *Renewable and Sustainable Energy Reviews*, vol. 167, p. 112723, 2022.
3. L. Sun, Z. Shang, Y. Xia, S. Bhowmick, and S. Nagarajaiah, "Review of bridge structural health monitoring aided by big data and artificial intelligence: From condition assessment to damage detection," *Journal of Structural Engineering*, vol. 146, no. 5, p. 04020073, 2020.
4. M. Esposito, M. Gherlone, and P. Marzocca, "External loads identification and shape sensing on an aluminum wing box: An integrated approach," *Aerospace Science and Technology*, vol. 114, p. 106743, 2021.
5. R. Lachmayer, I. Mozgova, W. Reimche, F. Colditz, G. Mroz, and P. Gottwald, "Technical inheritance: A concept to adapt the evolution of nature to product engineering," *Procedia Technology*, vol. 15, pp. 178–187, 2014.
6. S. Meyer zu Westerhausen, J. Schneider, and R. Lachmayer, "Automatic reliability assessment of data paths in component-integrated sensor networks," *Proceedings of the 33rd European Safety and Reliability Conference (ESREL 2023)*, p. 2223–2229, 2023.
7. R. Patton, "Fault detection and diagnosis in aerospace systems using analytical redundancy," *Computing & Control Engineering Journal*, vol. 2, pp. 127–136, May 1991.
8. J.-H. Bartels, T. Potthast, S. Möller, T. Grießmann, M. Beer, R. Rolfes, and S. Marx, "Robust SHM: Redundancy approach with different sensor integration levels for long life monitoring systems," in *Proceedings of the 11th European Workshop on Structural Health Monitoring (EWSHM 2024)*, vol. 29 of *7*, (Potsdam), pp. 1–10, NDT.net, June 2024.
9. T. Al-Zuriqat, C. Chillón Geck, K. Dragos, and K. Smarsly, "Adaptive Fault Diagnosis for Simultaneous Sensor Faults in Structural Health Monitoring Systems," *Infrastructures*, vol. 8, p. 39, Mar. 2023.
10. E. Lydakis, H. Koss, R. Brincker, and S. Amador, "Data-driven sensor fault diagnosis for vibration-based structural health monitoring under ambient excitation," *Measurement*, vol. 237, p. 115232, Sept. 2024.
11. G. McLachlan, "Mahalanobis distance," *Resonance*, 1999.
12. R. De Maesschalck, D. Jouan-Rimbaud, and D. Massart, "The mahalanobis distance," *Chemometrics and Intelligent Laboratory Systems*, vol. 50, no. 1, pp. 1–18, 2000.
13. Y. Wang, Q. Miao, E. Ma, K.-L. Tsui, and M. Pecht, "Online Anomaly Detection for Hard Disk Drives Based on Mahalanobis Distance," *IEEE Transactions on Reliability*, vol. 62, pp. 136–145, Mar. 2013.
14. S. Meyer zu Westerhausen, J.-H. Bartels, T. Potthast, M. Beer, S. Marx, and R. Lachmayer, "Strain data from saled three-point-bending test for sensor fault detection," 2025.